

Article

Not peer-reviewed version

A Spatial Econometric Analysis of Weather Effects on Milk Production

[Xinxin Fan](#) * and [Jiechao Ma](#)

Posted Date: 9 July 2024

doi: 10.20944/preprints202407.0676.v1

Keywords: weather condition; milk production; heat stress; spatial panel models.



Preprints.org is a free multidiscipline platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This is an open access article distributed under the Creative Commons Attribution License which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Article

A Spatial Econometric Analysis of Weather Effects on Milk Production

Xinxin Fan ^{1,*} and Jiechao Ma ²

¹ DOE Center for Advanced Bioenergy and Bioproducts Innovation (CABBI), University of Illinois at Urbana-Champaign, 1206 W. Gregory Drive, Urbana, IL 61801, USA; xinfan@illinois.edu

² Department of Biomedical Engineering, University of Illinois at Chicago, 1905 W. Taylor St. Chicago, IL 60612; jma48@uic.edu

* Correspondence: xinfan@illinois.edu

Abstract: Greenhouse gas (GHG) emission-induced climate change, particularly occurring since the mid-20th century has been considerably affecting short-term weather conditions, such as increasing weather variability, and incidence of extreme weather-related events. Milk production is sensitive to such changes. In this study, we use spatial panel econometric models, Spatial Error Model (SEM) and Spatial Durbin Model (SDM), with a panel dataset at the state-level varying over seasons, to estimate the relationship between weather indicators and milk productivity, in an effort to reduce the bias of omitted climatic variables that can be time-varying and spatially correlated and cannot be directly captured by conventional panel data models. We find an inverse U-shaped effect of summer heat stress on milk production per cow (MPC), indicating that milk production reacts positively to a low-level increase in summer heat stress, and then MPC declines as heat stress continues increasing beyond a threshold value of 72. Additionally, fall precipitation exhibits an inverse U-shaped effect on MPC, showing that milk yield increases at a decreasing rate until fall precipitation rises to 14 inches and then over that threshold milk yield declines at an increasing rate. We also find that, relative to conventional panel data models, spatial panel econometric models could improve prediction performance by leading to smaller in-sample and out-sample root mean squared errors. Our study contributes to the literature by exploring the feasibility of promising spatial panel models and resulting in estimating weather influences on milk productivity with high model predicting performance.

Keywords: weather condition; milk production; heat stress; spatial panel models

1. Introduction

The increasing concentration of greenhouse gases (GHGs) in earth's atmosphere is expected to increase air temperatures, weather variability, and the frequency of weather-related extreme events such as heat waves and freezes [1]. The literature indicates milk production, feed intake, reproductive efficiency and animal health are all sensitive to such changes [2]. Regional effects are expected to be uneven. Understanding impacts of weather condition changes on regional milk production in the U.S. is crucial for the U.S. agricultural sector and attracting much attention from researchers [3,4].

In this study, we use panel econometric models to estimate relationships between weather indicators and milk productivity. Panel data approaches have been widely utilized to analyze climatic effects on productivity as reviewed in Blanc and Schlenker [5]. However, such approaches may suffer from omitted variable biases [6]. In particular, time-varying omitted variables that are common across regions cannot be captured by regional fixed effects. Weather factors, such as wind or solar radiation, vary over time and are spatially correlated. When omitted such variables will lead to spatial correlated error terms. Spatial panel models have been developed to handle such issues [7–10]. To the best of our knowledge, we are not aware of any study that has applied spatial panel models

to examine the extent to which changes in weather condition can affect milk production to reduce omitted variable biases. The rest of the paper is organized as follows. Section 2 reviews related literature. The model structure, assumptions, and data are described in Section 3 and is followed by the model estimation results in Section 4. Conclusions and discussion are provided in Sections 5.

2. Literature Review

2.1. Weather and Milk Productivity

Heat stress and the zone of thermal comfort play an important role in livestock production and reproduction [11]. When conditions exceed the upper limit of that zone, livestock exhibit degraded performance [12]. West [13] and Lacetera et al. [14] indicate dairy cows are especially sensitive to heat stress exhibiting reduced feed intake, increased water intake, decreased meat and milk production, and altered birth rates. Ravagnolo, Misztal and Hoogenboom [15] suggest that a one unit increase in heat stress leads to about a 0.2 kg daily milk yield loss compared to a base of 26.3 kg. Mauger et al. [3] estimate climate is causing present-day US Holstein milk production losses of 1.9 percent and project that climate change could cause this to increase to 6.3 percent by 2100 generating a \$2.2 billion annual loss.

Heat stress arises from the combination of temperature, air movement, and humidity [11,16–18]. The Temperature Humidity Index (THI) is the most commonly used index [19,20] to quantify heat stress. There are several alternative THI formulae as summarized by Bohmanova et al. [16]. The determinants are dew point temperature, wet bulb temperature, relative humidity, wind speed, solar radiation and water vapor [21].

In this study, we use seasonal maximum and minimum THI calculated with the formula of Amundson et al. [22] and apply spatial panel models to relate it to milk production while also including other weather factors. Hammami et al. [23] show milk production exhibits an inverse U-shaped curve with respect to THI with the threshold falling in the range of 62 – 82. In particular, milk productivity is expected to increase at a decreasing rate when the THI increases before reaching a threshold level and then milk yield decreases at an increasing rate as the THI continues increasing.

2.2. Econometric Analysis of Climate Effects on Agricultural Production

There have been a number of panel econometric studies measuring weather impacts on agricultural productivity as reviewed in Blanc and Schlenker [5]. For crop yields, such studies include: Schlenker and Roberts [24], Deschênes and Greenstone [25], Miao, Khanna, and Huang [26], etc. Regionally, Mukherjee, Bravo-Ureta and De Vries [27] examine climatic impacts on southeastern U.S. milk yields, finding that THI has a significant non-linear negative effect. Qi, Bravo-Ureta and Cabrera [28] examine temperature and precipitation effects on Wisconsin dairy farm productivity and find those weather indicators have exerted deleterious effects and would further reduce milk output by 5 to 11% per year between 2020 and 2039. Perez-Mendez, Roibas and Wall [29] estimate effects of weather condition on Spanish milk production considering cow performance and forage supplies. But they find changes in weather mainly affect forage availability and the THI has no significant effect on milk production. Key and Sneeringer [30] examine heat stress in US major milk producing regions, finding it would depress milk production and cause national economic loss.

Although panel models control some forms of omitted variable bias [5,31], they do not control all forms. In particular omitting climate variables that are related across regions (e.g., vapor pressure deficit and wind speed) would bias estimation results [32,33]. This is a concern since climate variables inherently vary across time and are correlated across space [34]. Auffhammer et al. [35] argue that omission of such variables will cause spatially correlated residuals, which will then bias estimation results, and that the situation can be improved by using spatial panel models.

Several studies have employed spatial panel models in studying climate effects on crop yields. Schlenker, Hanemann and Fisher [9] use the Spatial Error Model (SEM), assuming spatially dependent error terms that are uncorrelated with independent variables. Ortiz-Bobea [10] uses the Spatial Durbin Model (SDM) that assumes spatially correlated error terms that are also correlated

with independent variables. Herein, this study utilizes both SEM and SDM, analyze their estimation results, and compares model performance with conventional panel data models to explore the feasibility of spatial panel models.

3. Materials and Methods

3.1. Model Specification

A standard panel model [36,37] can be expressed as follows:

$$y = X\beta + \mu \quad (1)$$

Where in our case y is annual milk production per cow; X is a vector of independent variables (i.e., weather indicators in our study); μ is an idiosyncratic error that is assumed to be independently identically distributed (iid).

We use two modeling approaches that improve estimations by controlling spatial correlation that arises due to omitted variables. The first is the SEM model of LeSage [38]. SEM assumes the omitted covariates are orthogonal to the independent variables but exhibit spatial dependence. That is in the above model $\mu = \gamma W\mu + \varepsilon$ or equivalently,

$$\mu = (I_n - \gamma W)^{-1} \varepsilon \quad (2)$$

where γ is a spatial dependence parameter; I_n is an identity matrix; W is a spatial weight matrix that reflects interactions in errors between regions; and ε is an iid error term. In this approach, equation (1) is changed to be:

$$y = X\beta + (I_n - \gamma W)^{-1} \varepsilon \quad (3)$$

Second is the SDM model of Cook, Hays and Franzese [39]. Therein the omitted variables are assumed to be correlated with the independent variables. In this case, we assume the error term in (3) is given by

$$\varepsilon = X\xi + v \quad (4)$$

where ξ is the interrelationship coefficient; and v is an iid error term. Then inserting (4) into (3), we obtain:

$$y = \gamma W y + X(\beta + \xi) + W X(-\gamma\beta) + v \quad (5)$$

For simplicity of notation, let

$$\tau = \beta + \xi, \varphi = -\gamma\beta \quad (6)$$

resulting in

$$y = \gamma W y + X\tau + W X\varphi + v \quad (7)$$

Equation (7) is the expression of the SDM estimating model and includes both the spatially lagged dependent variable and the independent variables. When $\xi = 0$ in equation (4) the SDM reduces to the SEM.

Following Belotti, Hughes and Piano Mortari [40], a unifying specification encompassing both cases is:

$$y_{nt} = \alpha + \rho W y_{nt} + X_{nt}\beta + W X_{nt}\theta + \phi_n + c_t + \mu_{nt} \quad (8)$$

$$\mu_{nt} = \lambda W \mu_{nt} + \varepsilon_{nt}$$

Where W is a spatial weight matrix; ρ, θ, λ are spatial correlation parameters; ϕ_n and c_t are the individual- and time-specific effects; μ_{nt} is a spatially correlated error; ε_{nt} is an idiosyncratic error.

In (8) if ρ and θ are all equal to zero, the model reduces to the SEM case with the spatial interaction in the error term as denoted by $\lambda W \mu_{nt}$, which means that milk production in one region could be affected by unobserved factors in neighboring regions.

On the other hand, if $\lambda = 0$, the model reduces to the SDM case, and β and θ are coefficients expressing the direct and indirect (spatial spillover) effects of the independent variables. Finally, if $\rho = \lambda = \theta = 0$, this reduces to a common panel model without spatial interaction.

In the spatial models, the matrix W reflects regional proximity. In this case, we follow Fischer and Getis [41] and set the elements to $1/n$ for each of n neighboring states and zero for non-

neighboring states. We also follow Taha et al. [42] and use the queen criterion to identify neighboring states.

3.2. Data

The above non-spatial and spatial panel models are estimated with the dependent variable being annual milk production per cow (MPC), and the explanatory variables being state level seasonal values of the palmer drought severity index (PDSI), total precipitation, and maximum and minimum THI. We use a dataset from 1950 to 2022 for the 48 contiguous US states. This yields 3504 observations and a balanced panel. Statistics computed over the data are shown in Table 1.

Data sources and manipulations are as follows:

Historical annual milk production: data on annual milk production per cow are drawn from United States Department of Agriculture’s National Agricultural Statistics Service Quick Stats database¹, and are measured in pounds per cow in a year (lbs/head).

Historical climatic data: state level daily palmer drought severity index (PDSI), total precipitation, minimum and maximum temperature, and minimum and maximum relative humidity (RH) data are drawn from National Oceanic and Atmospheric Administration (NOAA) [43]. These data are aggregated into 4 seasons (spring-March to May, summer-June to August, fall-September to November, and winter-December to February). Over these periods, PDSI is the average value, and the more negative the value the drier the climate is with positive values being wetter; precipitation data are the three-month total. Daily minimum temperature and maximum RH are used to calculate daily minimum THI (Min THI), whereas daily maximum THI (Max THI) are calculated using maximum temperature and minimum RH [44,45], following the THI formula of Amundson et al. [22] and Mader, Davis, and Brown-Brandl [17]. Seasonal Min THI and Max THI are computed by averaging the values across the days in the three-month period. Temperatures are measured in degrees Celsius, and precipitation is measured in inches. We use the data from 1950-2014 to execute model estimation and reserve data from 2015-2022 for out-of-sample testing.

Table 1. Statistical Summary over Historical Data (1950-2022).

Variable	# Obs.	Mean	Std. Dev.	Min	1.Quartile	2.Quartile	3.Quartile	Max
Log Milk Production per Cow	3504	4.1	0.2	3.4	3.9	4.1	4.2	4.4
Spring Precipitation	3504	9.7	4.4	0.3	6.6	9.6	12.5	31.1
Spring PDSI	3504	0.1	2.2	-7.5	-1.4	0.0	1.7	7.7
Spring Min THI	3504	40.1	7.8	23.5	34.0	39.3	45.5	63.3
Spring Max THI	3504	60.7	5.7	46.7	56.2	60.0	64.8	76.7
Summer Precipitation	3504	10.3	4.9	0.1	6.9	10.7	13.4	28.8
Summer PDSI	3504	0.1	2.4	-8.7	-1.5	0.2	1.9	9.1
Summer Min THI	3504	59.3	6.3	44.6	54.6	59.2	64.1	73.9
Summer Max THI	3504	74.7	4.2	64.8	71.2	74.5	77.7	89.1
Fall Precipitation	3504	8.8	4.3	0.5	5.3	8.8	11.7	24.5
Fall PDSI	3504	0.3	2.4	-7.9	-1.3	0.2	1.9	10.5
Fall Min THI	3504	43.0	7.1	26.5	37.6	42.5	47.9	66.2
Fall Max THI	3504	62.5	5.4	47.7	58.2	62.1	66.4	78.5
Winter Precipitation	3504	8.2	5.0	0.5	3.7	8.1	11.4	27.6
Winter PDSI	3504	0.2	2.0	-6.6	-1.1	0.2	1.5	6.8
Winter Min THI	3504	23.8	9.9	-3.5	16.9	23.8	30.3	53.1
Winter Max THI	3504	46.5	8.5	22.5	40.5	46.0	53.2	69.3

Note: PDSI denotes palmer drought severity index; THI denotes temperature humidity index

In our estimation, quadratic terms for the weather variables are included, following previous studies [46–48], as milk yield tends to be non-linearly correlated with a given weather variable. A linear and a quadratic time trend are also added as independent variables to capture "the effect of

¹ Please refer to <https://quickstats.nass.usda.gov/>

technological progress". The dependent variable – MPC is transformed into log form (as recommended by Mauldon [49] and Mosheim [50]), which helps stabilize the variance in the data [51].

4. Results

Estimations are done using conventional and spatial panel regression models. We estimate a pooled OLS, a fixed effects panel, spatial panel models (i.e., SEM and SDM).

4.1. Results without Spatial Interactions

Pooled OLS and fixed effects panel model results are summarized in Table 2. Therein most weather variables exhibit a U-shaped effect with a significant quadratic term. The fixed effects model fits better as the null hypothesis of no state-specific fixed effects is rejected at the 1% level using the standard F test. The climate effects in the pooled OLS model are generally larger, indicating neglecting regional fixed effects overstates the climate impact. The smaller results under the panel model likely occur since its fixed effects terms capture important regional omitted variables such as soils, elevation, topography, etc.

In the fixed effects panel model, the summer max THI exhibits an inverse U-shaped effect, meaning that holding other factors constant, MPC will increase as the THI value increases up to a threshold value, and then if the summer max THI increases beyond that threshold level MPC will decrease. This is generally consistent with findings from previous research [52].

Table 2. Pooled OLS and Fixed Effects Model Results.

Variable	Pooled OLS		Fixed Effects Model	
Spring Precipitation	-0.0060***	-0.0012	-0.0018	-0.0011
Spring Precipitation 2	0.0001**	0.0000	0.0001**	0.0000
Spring PDSI	0.0033**	-0.0014	-0.0020*	-0.0011
Spring PDSI 2	0.0005*	-0.0003	0.0002	-0.0002
Spring Min THI	0.0247***	-0.0041	0.0028	-0.0036
Spring Min THI 2	-0.0003***	-0.0001	-0.0001	0.0000
Spring Max THI	-0.0581***	-0.0110	-0.0322***	-0.0091
Spring Max THI 2	0.0004***	-0.0001	0.0003***	-0.0001
Summer Precipitation	-0.0121***	-0.0011	-0.0016	-0.0014
Summer Precipitation 2	0.0004***	0.0000	0.0000	0.0000
Summer PDSI	-0.0002	-0.0012	0.0009	-0.0010
Summer PDSI 2	0.0001	-0.0002	0.0005***	-0.0002
Summer Min THI	0.0412***	-0.0068	-0.0289***	-0.0084
Summer Min THI 2	-0.0004***	-0.0001	0.0002***	-0.0001
Summer Max THI	-0.0017	-0.0184	0.0476***	-0.0170
Summer Max THI 2	-0.0001	-0.0001	-0.0003***	-0.0001
Fall Precipitation	0.0058***	-0.0014	0.0030**	-0.0013
Fall Precipitation 2	-0.0002***	-0.0001	-0.0001**	0.0000
Fall PDSI	-0.0037***	-0.0010	-0.0014	-0.0009
Fall PDSI 2	-0.0003*	-0.0002	-0.0004**	-0.0002
Fall Min THI	0.0163***	-0.0037	-0.0167***	-0.0037
Fall Min THI 2	-0.0001**	0.0000	0.0002***	0.0000
Fall Max THI	-0.0155	-0.0100	0.0403***	-0.0087
Fall Max THI 2	0.0001	-0.0001	-0.0003***	-0.0001
Winter Precipitation	-0.0025***	-0.0009	-0.0004	-0.0009
Winter Precipitation 2	0.0000	0.0000	0.0000	0.0000
Winter PDSI	0.0005	-0.0013	0.0016	-0.0010
Winter PDSI 2	-0.0008**	-0.0003	-0.0006**	-0.0002
Winter Min THI	-0.0030***	-0.0012	-0.0039***	-0.0011
Winter Min THI 2	0.0001***	0.0000	0.0001***	0.0000
Winter Max THI	0.0130***	-0.0035	0.0153***	-0.0033
Winter Max THI 2	-0.0001***	0.0000	-0.0002***	0.0000
T1	0.0152***	-0.0002	0.0157***	-0.0002
T2	-0.0001***	0.0000	-0.0001***	0.0000
Constant	4.3068***	-0.5264	2.6282***	-0.5308
R-squared	0.9342		0.9587	

Note: PDSI denotes palmer drought severity index; THI denotes temperature humidity index; variable ending with 2 denotes the quadratic form of a given variable; the asterisks represent the probability that the coefficient differs from 0 and * notes significance at 10% level, ** at 5%, and *** at 1%.

4.2. Spatial Panel Model Results

The spatial panel models are relevant when there is spatial dependence in the error terms. We test this using Pesaran’s CD test [53,54] computed over the fixed effects panel model residuals. As a result, the no cross-regional dependence null hypothesis is rejected at the 1% level. Hence, it is appropriate to move on to estimation results from the spatial panel models.

The SEM and SDM estimation results are shown in Table 3. For the SEM, the spatial parameter λ is positive (0.67) and significant at the 1% level, implying a strong spatial dependence in the unobserved factors. The effects of a random shock in a specific region that transmit to its neighborhood can be estimated by multiplying λ with the corresponding spatial weights.

Table 3. SEM and SDM Estimation Results.

Variable	SEM		SDM			
	Main		Main		WX	
Spring Precipitation	-0.0024**	-0.0010	-0.0021*	-0.0011	0.0026	-0.0017
Spring Precipitation 2	0.0001***	0.0000	0.0001**	0.0000	-0.0001	-0.0001
Spring PDSI	-0.0005	-0.0010	-0.0002	-0.0010	-0.0010	-0.0014
Spring PDSI 2	-0.0001	-0.0002	-0.0002	-0.0002	0.0006**	-0.0003
Spring Min THI	0.0047	-0.0039	0.0066	-0.0044	-0.0088	-0.0062
Spring Min THI 2	-0.0001**	0.0000	-0.0001**	-0.0001	0.0001*	-0.0001
Spring Max THI	-0.0242**	-0.0094	-0.0165	-0.0103	0.0109	-0.0154
Spring Max THI 2	0.0002***	-0.0001	0.0002*	-0.0001	-0.0001	-0.0001
Summer Precipitation	-0.0022*	-0.0012	-0.0017	-0.0012	0.0039*	-0.0020
Summer Precipitation 2	0.0001*	0.0000	0.0001	0.0000	-0.0002**	-0.0001
Summer PDSI	0.0005	-0.0009	0.0004	-0.0009	0.0000	-0.0013
Summer PDSI 2	0.0003**	-0.0001	0.0004**	-0.0001	-0.0002	-0.0002
Summer Min THI	0.0242***	-0.0084	0.0352***	-0.0090	-0.0812***	-0.0131
Summer Min THI 2	-0.0002***	-0.0001	-0.0003***	-0.0001	0.0007***	-0.0001
Summer Max THI	-0.0447***	-0.0158	-0.0474***	-0.0165	0.1444***	-0.0250
Summer Max THI 2	0.0003***	-0.0001	0.0003***	-0.0001	-0.0010***	-0.0002
Fall Precipitation	0.0001	-0.0012	-0.0004	-0.0012	0.0036*	-0.0018
Fall Precipitation 2	0.0000	0.0000	0.0000	0.0000	-0.0001**	-0.0001
Fall PDSI	0.0008	-0.0008	0.0012	-0.0008	-0.0033***	-0.0012
Fall PDSI 2	-0.0004**	-0.0001	-0.0003**	-0.0001	0.0004*	-0.0002
Fall Min THI	-0.0029	-0.0041	0.0041	-0.0046	-0.0164***	-0.0062
Fall Min THI 2	0.0000	0.0000	-0.0001	-0.0001	0.0002***	-0.0001
Fall Max THI	0.0124	-0.0094	0.0065	-0.0106	0.0228	-0.0149
Fall Max THI 2	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002	-0.0001
Winter Precipitation	-0.0015	-0.0010	-0.0020**	-0.0010	0.0015	-0.0014
Winter Precipitation 2	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001
Winter PDSI	-0.0002	-0.0010	-0.0005	-0.0010	0.0018	-0.0014
Winter PDSI 2	0.0001	-0.0002	0.0002	-0.0002	-0.0010***	-0.0003
Winter Min THI	-0.0009	-0.0013	0.0013	-0.0015	-0.0039*	-0.0020
Winter Min THI 2	0.0001**	0.0000	0.0000	0.0000	0.0001	0.0000
Winter Max THI	0.0087**	-0.0037	0.0047	-0.0043	0.0037	-0.0060
Winter Max THI 2	-0.0001***	0.0000	-0.0001	0.0000	0.0000	-0.0001
T1	0.0155***	-0.0003	0.0059***	-0.0003		
T2	-0.0001***	0.0000	-0.0000***	0.0000		
λ	0.6651***	-0.0142				
ρ			0.6239***	-0.0148		
R-squared	0.8932		0.8818			

Note: PDSI denotes palmer drought severity index; THI denotes temperature humidity index; variable ending with 2 denotes the quadratic form of a given variable; the asterisks represent the probability that the coefficient differs from 0 and * notes significance at 10% level, ** at 5%, and *** at 1%.

Now turning to the SDM results, the spatial autoregressive parameter ρ (0.62), which reflects the average intensity of the spatial intercorrelation [38], is also significant and indicating a strong spatial dependence. The spatially lagged independent variables (WX) measure the indirect impacts on MPC in one region arising from changes in variables X from its neighbored regions [55]. Following LeSage and Dominguez [56] and Sarrias [57], weather influences can be split up considering the direct in-region effects of X and the indirect effects translated in from adjacent regions. In particular, equation (7) can be rewritten to equation (9):

$$y_{nt} = \sum_{k=1}^K (I_n - \gamma W)^{-1} (I_n \tau_k + W \varphi_k) x_{k,nt} + (I_n - \gamma W)^{-1} v_{nt} \quad (9)$$

and the effects of the independent variables can be computed as

$$\begin{aligned} S_k &= \frac{\partial y_{nt}}{\partial x_{k,nt}} = (I_n - \gamma W)^{-1} (I_n \tau_k + W \varphi_k) \\ &= (I_n - \gamma W)^{-1} \begin{bmatrix} \tau_k & w_{12} \varphi_k & \cdots & w_{1n} \varphi_k \\ w_{21} \varphi_k & \tau_k & \cdots & w_{2n} \varphi_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} \varphi_k & w_{n2} \varphi_k & \cdots & \tau_k \end{bmatrix} \end{aligned}$$

Where n identifies region, $k = 1, \dots, K$ denotes the set of independent variables, and S_k the effect on production across regions of variations in the k^{th} independent variable. In turn, the average direct effect is the average of the diagonal elements of S_k , and the average total effect is equal to $n^{-1} \iota_n' S_k \iota_n$, which ι_n is a vector of 1's. The indirect effect is the total effect minus the direct effect.

For our estimation the empirical SDM direct and indirect impacts are shown in Table 4, along with the SEM results for comparison. Overall, the SDM estimates show that more weather variables exert significant effects, relative to the SEM results. Summer max THI again exhibits an inverse U-shape total effect on MPC; thereby milk yield increases as the summer max THI increases toward a threshold value, and then yield declines as this THI is higher than the threshold moving extreme heat stress, which coincides with the findings in Hammami et al. [23]. We also find a significant indirect effect of summer max THI, which represents the spatial spillover impacts on MPC in a state from changes in summer max THI of its nearby states [10].

Additionally, the linear and quadratic time trend variables were included here to capture the effects of factors like technological improvements changing over time, such as developments in animal genetics, nutrition and animal management. In both spatial models and the pooled OLS and non-spatial fixed effects panel model, the linear time trend is significant and positive showing increasing MPC over time, while the quadratic term is negative, showing diminishing technological progress over time.

Table 4. Direct and Indirect Effects of Climate Variables from SDM (vs. SEM results).

Variable	SDM						SEM	
	Direct		Indirect		Total			
Spring Precipitation	-0.0018*	-0.0011	0.0030	-0.0032	0.0012	-0.0034	-0.0024**	-0.0010
Spring Precipitation 2	0.0001*	0.0000	-0.0001	-0.0001	0.0000	-0.0001	0.0001***	0.0000
Spring PDSI	-0.0004	-0.0009	-0.0029	-0.0030	-0.0033	-0.0033	-0.0005	-0.0010
Spring PDSI 2	-0.0001	-0.0002	0.0012*	-0.0006	0.0010	-0.0007	-0.0001	-0.0002
Spring Min THI	0.0056	-0.0039	-0.0115	-0.0111	-0.0059	-0.0109	0.0047	-0.0039
Spring Min THI 2	-0.0001**	0.0000	0.0002	-0.0001	0.0001	-0.0001	-0.0001**	0.0000
Spring Max THI	-0.0164*	-0.0094	0.0007	-0.0284	-0.0157	-0.0280	-0.0242**	-0.0094
Spring Max THI 2	0.0002**	-0.0001	0.0000	-0.0002	0.0001	-0.0002	0.0002***	-0.0001
Summer Precipitation	-0.0010	-0.0012	0.0067	-0.0042	0.0057	-0.0046	-0.0022*	-0.0012
Summer Precipitation 2	0.0000	0.0000	-0.0003**	-0.0001	-0.0003*	-0.0002	0.0001*	0.0000
Summer PDSI	0.0003	-0.0008	0.0008	-0.0026	0.0011	-0.0029	0.0005	-0.0009
Summer PDSI 2	0.0004**	-0.0002	0.0001	-0.0005	0.0005	-0.0006	0.0003**	-0.0001
Summer Min THI	0.0210**	-0.0085	-0.1449***	-0.0238	-0.1239***	-0.0254	0.0242***	-0.0084
Summer Min THI 2	-0.0002***	-0.0001	0.0012***	-0.0002	0.0010***	-0.0002	-0.0002***	-0.0001
Summer Max THI	-0.0213	-0.0159	0.2808***	-0.0485	0.2594***	-0.0543	-0.0447***	-0.0158
Summer Max THI 2	0.0001	-0.0001	-0.0019***	-0.0003	-0.0018***	-0.0004	0.0003***	-0.0001
Fall Precipitation	0.0004	-0.0012	0.0080**	-0.0036	0.0084**	-0.0038	0.0001	-0.0012
Fall Precipitation 2	0.0000	0.0000	-0.0003**	-0.0001	-0.0003**	-0.0001	0.0000	0.0000
Fall PDSI	0.0006	-0.0008	-0.0063**	-0.0025	-0.0056**	-0.0027	0.0008	-0.0008
Fall PDSI 2	-0.0003**	-0.0001	0.0003	-0.0004	0.0000	-0.0005	-0.0004**	-0.0001
Fall Min THI	0.0007	-0.0044	-0.0336***	-0.0106	-0.0328***	-0.0103	-0.0029	-0.0041
Fall Min THI 2	0.0000	-0.0001	0.0004***	-0.0001	0.0004***	-0.0001	0.0000	0.0000
Fall Max THI	0.0128	-0.0098	0.0658**	-0.0258	0.0785***	-0.0251	0.0124	-0.0094
Fall Max THI 2	-0.0001	-0.0001	-0.0005***	-0.0002	-0.0007***	-0.0002	-0.0001	-0.0001
Winter Precipitation	-0.0020**	-0.0010	0.0005	-0.0027	-0.0015	-0.0028	-0.0015	-0.0010
Winter Precipitation 2	0.0000	0.0000	0.0001	-0.0001	0.0001	-0.0001	0.0000	0.0000
Winter PDSI	-0.0001	-0.0010	0.0038	-0.0029	0.0037	-0.0032	-0.0002	-0.0010
Winter PDSI 2	0.0000	-0.0002	-0.0020***	-0.0007	-0.0019***	-0.0007	0.0001	-0.0002
Winter Min THI	0.0006	-0.0014	-0.0076**	-0.0034	-0.0070**	-0.0033	-0.0009	-0.0013
Winter Min THI 2	0.0000	0.0000	0.0001*	-0.0001	0.0002**	-0.0001	0.0001**	0.0000
Winter Max THI	0.0062	-0.0038	0.0163*	-0.0098	0.0225**	-0.0094	0.0087**	-0.0037
Winter Max THI 2	-0.0001**	0.0000	-0.0002	-0.0001	-0.0003**	-0.0001	-0.0001***	0.0000
T1	0.0067***	-0.0002	0.0089***	-0.0003	0.0156***	-0.0003	0.0155***	-0.0003
T2	-0.0000***	0.0000	-0.0001***	0.0000	-0.0001***	0.0000	-0.0001***	0.0000

Note: PDSI denotes palmer drought severity index; THI denotes temperature humidity index; variable ending with 2 denotes the quadratic form of a given variable; the asterisks represent the probability that the coefficient differs from 0 and * notes significance at 10% level, ** at 5%, and *** at 1%.

These results can be illustrated graphically. Figure 1 displays the relationship between a given weather factor with the MPC when holding other variables constant. Figure 1a shows the percentage changes in MPC as the summer max THI increases by one unit based on the historical minimum (64.8). The summer max THI has an inverse U-shaped effect with a threshold value of 72. Above that threshold, the increase in the summer max THI will decrease MPC. However, if the THI is below this threshold value, its increase will positively affect the MPC, because in that lower THI range, warmer environment would benefit livestock production as found in Du Preez et al. [58] and Correa-Calderon et al. [59]. Nationally, most regions experienced MPC reduction induced by heat stress as the comparison between the historical summer max THI observations and the threshold shows more than 2/3 of past observations exceed the threshold value of 72.

The effects of other weather factors are also plotted in Figure 1. Fall precipitation also exhibits an inverse U-shaped relationship with MPC (Figure 1b), that is, MPC increases at a decreasing rate as fall precipitation rises up to the threshold value of 14 inches. Beyond that threshold value, MPC declines at an increasing rate. Generally, since about 90% of the fall precipitation observations are smaller than the threshold, to some extent, more precipitation would increase MPC perhaps reflecting added forage availability [60,61]. For winter PDSI (Figure 1c), its total effect also shows an inverse U-shape with a threshold value of 0. This implies as PDSI rises indicating less drought, MPC tends to

increase, but as PDSI continues increasing to be higher than the threshold value of 0, then MPC falls as environmental condition gets wetter. These results agree with previous literature [62,63].

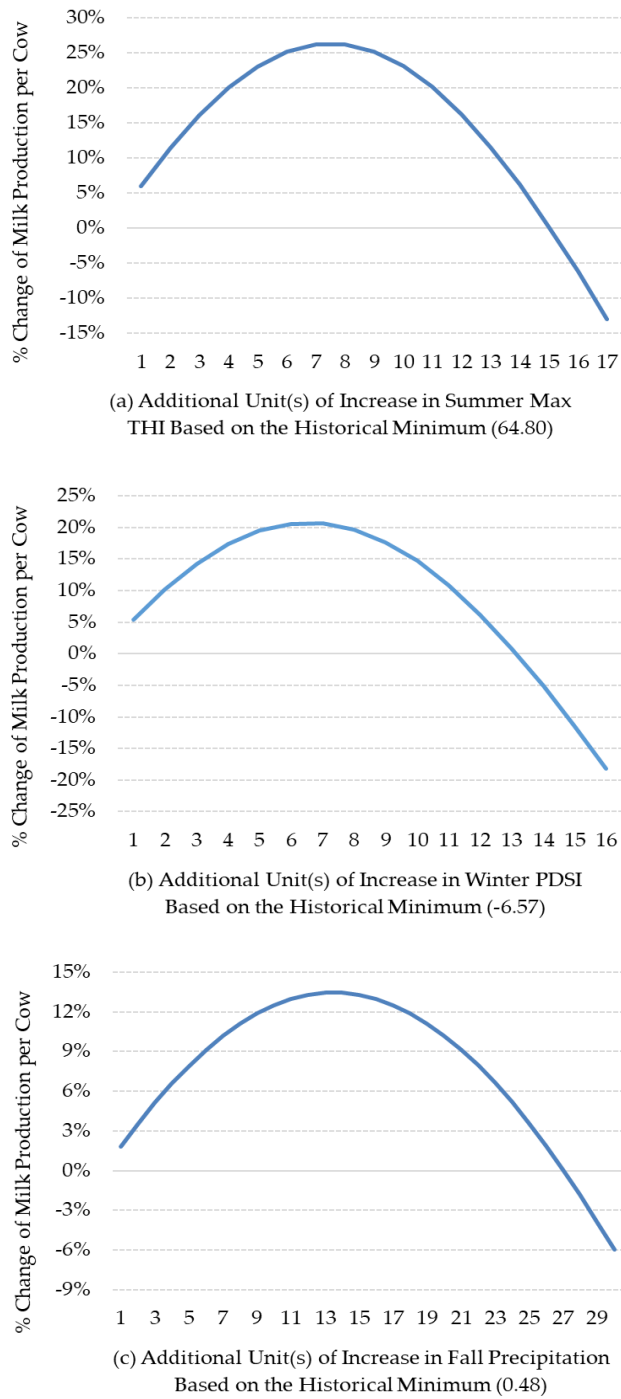


Figure 1. Relationship between Milk Production per Cow and Weather Factors: (a) Summer Max THI; (b) Winter PDSI; (c) Fall Precipitation.

4.3. Model Comparison

Now we compare model performance by examining the in and out of sample model fit using the root mean squared error (RMSE) as the criterion [64]. The in-sample RMSE is computed with the data from 1950 to 2014, assessing how effective the models are in reproducing data, whereas the out-of-sample RMSE, calculated by the holdout dataset from 2015 to 2022, is to evaluate the forecasting accuracy of the models on a new dataset of independent variables [65]. The results in Table 5 show that the estimates from the spatial models outperform that from the conventional panel data models.

Table 5. Model Forecasting Performance.

Model	In-sample RMSE	Out-of-sample RMSE
	(1950-2014)	(2015-2022)
Pooled OLS Model	0.051	0.060
Fixed Effects Model	0.068	0.067
SEM	0.039	0.048
SDM	0.037	0.051

Next, we statistically test differentiating parameters using a Wald test. First, we test whether the SEM spatial dependence (λ) factor is significantly different from zero and find it is at the 1% confidence level. In turn, we conclude the SEM model is more appropriate than the fixed effects panel model and that it is important to incorporate spatial correlation.

Next, we test whether $\varphi + \gamma\tau = 0$, which if so, means that SDM reduces to SEM [66]. This is also rejected at the 1% level, which indicates that SDM performs better than SEM. Thus, it is important to incorporate the correlation between the independent and the omitted variables.

5. Conclusions and Discussion

Our estimation results show changes in weather conditions influence the U.S. milk production (on a per cow basis). Summer heat stress, as measured by summer max THI, exerts a significant effect on milk production. They are estimated to have an inverse U-shaped relationship with a threshold value of 72, when holding other variables constant; below this threshold, milk yield increases as the summer max THI rises, but when this THI continues increasing to be higher than that threshold value, milk productivity declines, which are aligned with findings by Renaudeau et al. [52]. Fall precipitation and winter drought conditions also exert an inverse U-shaped effect with threshold values of 14 inches and 0 on the PDSI scale, respectively. In essence, regarding such inverse U-shaped relationship, an extreme weather condition, such as moving toward too much or too little rain, will negatively affect milk production.

On the methodological side, we use several model forms in an effort to reduce omitted variable bias and improve model fit. The results strongly support spatial panel models, particularly the SDM, that can control spatial correlation that arises due to omitted weather variables. It should be noted that the spatial panel models are designed to reduce the effect of omitted spatially pervasive forces but does not eliminate that bias. Therefore, in subsequent research, it would be good to explore improved model specifications and include more climate related variables.

Author Contributions: Conceptualization, X.F. and J.M.; methodology, X.F.; software, X.F.; validation, X.F. and J.M.; formal analysis, X.F.; investigation, X.F.; resources, X.F.; data curation, J.M.; writing—original draft preparation, X.F.; writing—review and editing, X.F. and J.M.; visualization, X.F. and J.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in the present study are available from the corresponding author on reasonable request, provided no ethical, legal, or privacy issues are raised.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. IPCC. Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama, Eds.). Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022, 3056 pp., doi:10.1017/9781009325844.
2. Hristov, A.N.; Degaetano, A.T.; Rotz, C.A.; Hoberg, E.; Skinner, R.; Felix, T.; Li, H.; Patterson, P.H.; Roth, G.; Hall, M.; et al. Climate Change Effects on Livestock in the Northeast US and Strategies for Adaptation. *Clim. Change* **2018**, *146*, 33–45, doi:10.1007/s10584-017-2023-z.
3. Thornton, P.K.; Van de Steeg, J.; Notenbaert, A.; Herrero, M. The Impacts of Climate Change on Livestock and Livestock Systems in Developing Countries: A Review of What We Know and What We Need to Know. *Agric. Syst.* **2009**, *101*, 113–127, doi:10.1016/j.agsy.2009.05.002.
4. Mauger, G.; Bauman, Y.; Nennich, T.; Salathé, E. Impacts of Climate Change on Milk Production in the United States. *The Prof. Geogr.* **2015**, *67*, 121–131, doi: 10.1080/00330124.2014.921017.
5. Blanc, E.; Schlenker, W. The Use of Panel Models in Assessments of Climate Impacts on Agriculture. *Rev. Environ. Econ. Policy* **2017**, *11*, 258–279, doi:10.1093/reep/rex016.
6. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT press, **2010**.
7. Mur, J.; Angulo, A. *A Closer Look at the Spatial Durbin Model*; ERS conference papers; European Regional Science Association, 2005;
8. Fingleton, B.; López-Bazo, E. Empirical Growth Models with Spatial Effects. *Pap. Reg. Sci.* **2006**, *85*, 177–198, doi: 10.1111/j.1435-5957.2006.00074.x.
9. Schlenker, W.; Hanemann, W.M.; Fisher, A.C. The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *The Rev. Econ. Stat.* **2006**, *88*, 113–125, doi:10.1162/rest.2006.88.1.113.
10. Ortiz-Bobea, A. The Impacts of Climate Change on US Agriculture: Accounting for Omitted Spatial Dependence in the Hedonic Approach. 2015. Available at: <https://www.aeaweb.org/conference/2016/retrieve.php?pdfid=361> (accessed on 05/06/2020)
11. National Research Council *A Guide to Environmental Research on Animals*; National Academies, 1971;
12. Klinedinst, P.L.; Wilhite, D.A.; Hahn, G.L.; Hubbard, K.G. The Potential Effects of Climate Change on Summer Season Dairy Cattle Milk Production and Reproduction. *Clim. Change* **1993**, *23*, 21–36, doi: 10.1007/BF01092679.
13. West, J.W. Effects of Heat-Stress on Production in Dairy Cattle. *J. Dairy Sci.* **2003**, *86*, 2131–2144, doi: 10.3168/jds.S0022-0302(03)73803-X.
14. Lacetera, N.; Bernabucci, U.; Ronchi, B.; Nardone, A. Physiological and Productive Consequences of Heat Stress. The Case of Dairy Ruminants. In Proceedings of the Proceedings of the Symposium on interaction between Climate and Animal Production: EAAP Technical Series; 2003; Vol. 7, pp. 45–60.
15. Ravagnolo, O.; Misztal, I.; Hoogenboom, G. Genetic Component of Heat Stress in Dairy Cattle, Development of Heat Index Function. *J. Dairy Sci.* **2000**, *83*, 2120–2125, doi: 10.3168/jds.S0022-0302(00)75094-6.
16. Bohmanova, J.; Misztal, I.; Cole, J.B. Temperature-Humidity Indices as Indicators of Milk Production Losses Due to Heat Stress. *J. Dairy Sci.* **2007**, *90*, 1947–1956, doi: 10.3168/jds.2006-513.
17. Mader, T.L.; Davis, M.S.; Brown-Brandl, T. Environmental Factors Influencing Heat Stress in Feedlot Cattle. *J. Anim. Sci.* **2006**, *84*, 712–719, doi: 10.2527/2006.843712x.
18. Gantner, V.; Mijić, P.; Jovanovac, S.; Raguž, N.; Bobić, T.; Kuterovac, K. Influence of Temperature-Humidity Index (THI) on Daily Production of Dairy Cows in Mediterranean Region in Croatia. In *Animal farming and environmental interactions in the Mediterranean region*; Wageningen Academic, 2011; pp. 71–78.
19. Igono, M.O.; Bjotvedt, G.; Sanford-Crane, H.T. Environmental Profile and Critical Temperature Effects on Milk Production of Holstein Cows in Desert Climate. *Int. J. Biometeorol.* **1992**, *36*, 77–87, doi: 10.1007/BF01208917.

20. Mayer, D.G.; Davison, T.; McGowan, M.R.; Young, B.A.; Matschoss, A.L.; Hall, A.B.; Goodwin, P.J.; Jonsson, N.N.; Gaughan, J.B. Extent and Economic Effect of Heat Loads on Dairy Cattle Production in Australia. *Aust. Vet. J.* **1999**, *77*, 804–808, doi: 10.1111/j.1751-0813.1999.tb12950.x.
21. Mader, T. I.; Johnson, L.J.; Gaughan, J.B. A Comprehensive Index for Assessing Environmental Stress in Animals. *J. Anim. Sci.* **2010**, *88*, 2153–2165, doi: 10.2527/jas.2009-2586.
22. Amundson, J.L.; Mader, T.L.; Rasby, R.J.; Hu, Q.S. Environmental Effects on Pregnancy Rate in Beef Cattle. *J. Anim. Sci.* **2006**, *84*, 3415–3420, doi: 10.2527/jas.2005-611.
23. Hammami, H.; Bormann, J.; M'hamdi, N.; Montaldo, H.H.; Gengler, N. Evaluation of Heat Stress Effects on Production Traits and Somatic Cell Score of Holsteins in a Temperate Environment. *J. Dairy Sci.* **2013**, *96*, 1844–1855, doi: 10.3168/jds.2012-5947.
24. Schlenker, W.; Roberts, M.J. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *PNAS* **2009**, *106*, 15594–15598, doi:10.1073/pnas.0906865106.
25. Deschênes, O.; Greenstone, M. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply. *Am. Econ. Rev.* **2012**, *102*, 3761–3773, doi: 10.1257/aer.102.7.3761.
26. Miao, R.; Khanna, M.; Huang, H. Responsiveness of Crop Yield and Acreage to Prices and Climate. *Am. J. Agric. Econ.* **2016**, *98*, 191–211, doi:10.1093/ajae/aav025.
27. Mukherjee, D.; Bravo-Ureta, B.E.; De Vries, A. Dairy Productivity and Climatic Conditions: Econometric Evidence from Southeastern United States. *Aust. J. Agric. Econ.* **2013**, *57*, 123–140, doi: 10.1111/j.1467-8489.2012.00603.x.
28. Qi, L.; Bravo-Ureta, B.E.; Cabrera, V.E. From Cold to Hot: Climatic Effects and Productivity in Wisconsin Dairy Farms. *J. Dairy Sci.* **2015**, *98*, 8664–8677, doi: 10.3168/jds.2015-9536.
29. Perez-Mendez, J.A.; Roibas, D.; Wall, A. The Influence of Weather Conditions on Dairy Production. *Agric. Econ.* **2019**, *50*, 165–175, doi: 10.1111/agec.12474.
30. Key, N.; Sneeringer, S. Potential Effects of Climate Change on the Productivity of U.S. Dairies. *Am. J. Agric. Econ.* **2014**, *96*, 1136–1156, doi: 10.1093/ajae/aau002.
31. Schlenker, W.; Hanemann, W.M.; Fisher, A.C. Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *Am. Econ. Rev.* **2005**, *95*, 395–406, doi: 10.1257/0002828053828455.
32. Hsiang, S.M.; Narita, D. Adaptation to Cyclone Risk: Evidence from the Global Cross-Section. *Clim. Change Econ.* **2012**, *3*, 1250011, doi: 10.1142/S201000781250011X.
33. Zhang, P.; Zhang, J.; Chen, M. Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other than Temperature and Precipitation. *J. Environ. Econ. Manag.* **2017**, *83*, 8–31, doi:10.1016/j.jeem.2016.12.001.
34. Auffhammer, M.; Schlenker, W. Empirical Studies on Agricultural Impacts and Adaptation. *Energy Econ.* **2014**, *46*, 555–561, doi: 10.1016/j.eneco.2014.09.010.
35. Auffhammer, M.; Hsiang, S.M.; Schlenker, W.; Sobel, A. Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Rev. Environ. Econ. Policy* **2013**, *7*, 181–198, doi:10.1093/reep/ret016.
36. Bramati, M.C.; Croux, C. Robust Estimators for the Fixed Effects Panel Data Model. *The Econom. J.* **2007**, *10*, 521–540, doi: 10.1111/j.1368-423X.2007.00220.x.
37. Sarker, M.A.R.; Alam, K.; Gow, J. Assessing the Effects of Climate Change on Rice Yields: An Econometric Investigation Using Bangladeshi Panel Data. *Econ. Anal. and Policy* **2014**, *44*, 405–416, doi: 10.1016/j.eap.2014.11.004.
38. LeSage, J.P. An Introduction to Spatial Econometrics. *Revue D'économie Industrielle* **2008**, *19*–44, doi: 10.4000/rei.3887.
39. Cook, S.J.; Hays, J.C.; Franzese, R.J. Chapter 39: Model Specification and Spatial Interdependence. In Book *The SAGE Handbook of Research Methods in Political Science and International Relations*; Luigi Curini and Robert Franzese, Eds.; SAGE, London 2020; pp. 730-747. doi: 10.4135/9781526486387.n42.
40. Belotti, F.; Hughes, G.; Piano Mortari, A. *Xsmle: A Stata Command for Spatial Panel-Data Models Estimation*; Stata Users Group, 2013.

41. Fischer, M.M.; Getis, A. *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*; Springer Berlin Heidelberg: Berlin, Heidelberg, **2010**; ISBN 978-3-642-03646-0.
42. Taha, R.; Dietrich, J.; Dehnhardt, A.; Hirschfeld, J. Scaling Effects in Spatial Multi-Criteria Decision Aggregation in Integrated River Basin Management. *Water* **2019**, *11*, 355, doi: 10.3390/w11020355.
43. National Oceanic Atmospheric Administration *Archive of Weather Data.*; 2018;
44. St-Pierre, N.R.; Cobanov, B.; Schnitkey, G. Economic Losses from Heat Stress by US Livestock Industries. *J. Dairy Sci.* **2003**, *86*, E52–E77.
45. Bernabucci, U.; Biffani, S.; Buggiotti, L.; Vitali, A.; Lacetera, N.; Nardone, A. The Effects of Heat Stress in Italian Holstein Dairy Cattle. *J. Dairy Sci.* **2014**, *97*, 471–486, doi: 10.3168/jds.2013-6611.
46. Shakoor, U.; Saboor, A.; Ali, I.; Mohsin, A.Q. Impact of Climate Change on Agriculture: Empirical Evidence from Arid Region. *Pak. J. Agri. Sci* **2011**, *48*, 327–333.
47. Lee, J.; Nadolnyak, D.A.; Hartarska, V.M. Impact of Climate Change on Agricultural Production in Asian countries: Evidence from Panel Study. In Proceedings of the Southern Agricultural Economics Association 2012 Annual Meeting, Birmingham, AL, USA, 4–7 February 2012, doi: 10.22004/ag.econ.119808.
48. Lagat, P.; Nyangena, J. The Effects of Climate Variability on Livestock Production in Kenya. *J. Agric. Policy* **2018**, *1*, 58–79.
49. Mauldon, R.G. An Econometric Analysis of the Supply of Livestock Products and Demand for Feed Grains. PhD Thesis, Department of Economics, Iowa State University, 1962.
50. Mosheim, R. *A Quarterly Econometric Model for Short-Term Forecasting of the US Dairy Industry*; Economic Research Service, United States Department of Agriculture, 2012.
51. Lütkepohl, H.; Xu, F. The Role of the Log Transformation in Forecasting Economic Variables. *Empir. Econ.* **2012**, *42*, 619–638, doi: 10.1007/s00181-010-0440-1.
52. Renaudeau, D.; Collin, A.; Yahav, S.; De Babilio, V.; Gourdine, J.L.; Collier, R.J. Adaptation to Hot Climate and Strategies to Alleviate Heat Stress in Livestock Production. *Animal* **2012**, *6*, 707–728, doi:10.1017/S1751731111002448.
53. Pesaran, M.H. Testing Weak Cross-Sectional Dependence in Large Panels. *Econom. Rev.* **2015**, *34*, 1089–1117, doi: 10.1080/07474938.2014.956623.
54. Pesaran, M.H. General Diagnostic Tests for Cross-Sectional Dependence in Panels. *Empir. Econ.* **2021**, *60*, 13–50, doi: 10.1007/s00181-020-01875-7.
55. Sheng, M.; Sharp, B. Influence of Urban Forms on Transit Behaviour in the Auckland Region: A Spatial Durbin Analysis. In Proceedings of the The 54th Annual Conference of New Zealand Association of Economists; **2013**.
56. LeSage, J.P.; Dominguez, M. The Importance of Modeling Spatial Spillovers in Public Choice Analysis. *Public Choice* **2012**, *150*, 525–545, doi: 10.1007/s11127-010-9714-6.
57. Sarrias, M. Class Notes and Slides of Spatial Econometrics 2017.
58. Du Preez, J.H.; Hattingh, P.J.; Giesecke, W.H.; Eisenberg, B.E. Heat Stress in Dairy Cattle and Other Livestock under Southern African Conditions. III. Monthly Temperature-Humidity Index-Mean Values and Their Significance in the Performance of Dairy Cattle. *Onderstepoort J. vet. Res.* **1990**, *57*, 243–248.
59. Correa-Calderon, A.; Armstrong, D.; Ray, D.; DeNise, S.; Enns, M.; Howison, C. Thermoregulatory Responses of Holstein and Brown Swiss Heat-Stressed Dairy Cows to Two Different Cooling Systems. *Int. J. Biometeorol.* **2004**, *48*, 142–148, doi:10.1007/s00484-003-0194-y.
60. Arrebola, F.A.; Abecia, J.A.; Forcada, F.; Garcia, A.; Martí, R.A.; Mesa, O. Effects of Annual Rainfall and Farm on Lamb Production after Treatment with Melatonin Implants in Merino Sheep: A 4-Year Study. *N. Zeal. Vet. J.* **2009**, *57*, 141–145, doi: 10.1080/00480169.2009.36893.
61. Abecia, J.A.; Garcia, A.; Castillo, L.; Palacios, C. The Effects of Weather on Milk Production in Dairy Sheep Vary by Month of Lambing and Lactation Phase. *J. Anim. Behav. Biometeorol.* **2017**, *5*, 56–63, doi: 10.31893/2318-1265jabb.v5n2p56-63.
62. Blanc, É. The Impact of Climate Change on Crop Production in Sub-Saharan Africa. PhD Thesis, University of Otago, 2011.

63. Popoola, O.P.; Dawodu, O.O.; Yusuf, O.O. Quadratic Regression and Factorial Analysis on the Effect of Climatic Elements on Global Food Production and Land Nutrients in Africa. *Annals. Comput. Sci. Series* **2018**, *16*.
64. Chai, T.; Kim, H.-C.; Lee, P.; Tong, D.; Pan, L.; Tang, Y.; Huang, J.; McQueen, J.; Tsidulko, M.; Stajner, I. Evaluation of the United States National Air Quality Forecast Capability Experimental Real-Time Predictions in 2010 Using Air Quality System Ozone and NO₂ Measurements. *Geosci. Model Dev.* **2013**, *6*, 1831–1850, doi:10.5194/gmd-6-1831-2013.
65. Tashman, L.J. Out-of-Sample Tests of Forecasting Accuracy: An Analysis and Review. *Int. J. Forecast.* **2000**, *16*, 437–450, doi: 10.1016/S0169-2070(00)00065-0.
66. Mur, J.; Angulo, A. Model Selection Strategies in a Spatial Setting: Some Additional Results. *Reg. Sci. Urban Econ.* **2009**, *39*, 200–213, doi:10.1016/j.regsciurbeco.2008.05.018.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.